

Applications of Operations Research in Real-Life Scenarios: A Literature-Based Analytical Study

Topic: Production Planning Under Limited Resources (Linear Programming Problems)

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Abstract

No production unit ever has unlimited inputs. Its stock of raw material, the hours its machines can run, the size of its workforce and the room in its stores are all fixed for the month, yet a decision still has to be taken on how much of every product to turn out. In this report we look at how Operations Research (OR), and specifically linear programming (LP), supports that decision, using two published case studies of manufacturers in Nigeria. Solaja et al. (2019) work out a monthly output plan for a firm that makes animal feed, and Adebisi, Amole and Soile (2014) choose the output mix for a paint maker selling five products. Each study is examined for its business setting, what the model tries to achieve, the limits and assumptions it uses, how it was solved, and what it does well or poorly. We then write down a general LP model for production planning. As our own contribution, we entered the numbers printed in both papers into a solver, solved them again, and ran several what-if cases on the feed data to see how the best plan shifts when the rules or the supply of inputs are changed.

1. Introduction to OR and the Problem Type

1.1 Operations Research in brief

Put simply, OR is the use of quantitative models to reach better decisions when money, time, materials or capacity are in short supply. The work normally begins by pinning down the business question clearly. The question is then translated into a model with three ingredients: the choices open to the decision-maker, a single measure of success that should be pushed up or down, and the restrictions no plan may break. After the model is solved, either to optimality or approximately, its answer is compared with the real situation before it is used. Common OR techniques include LP, transportation and assignment, networks, PERT/CPM and queueing theory. The shared benefit is that choices once made by rule of thumb become explicit, open to checking and easy to repeat.

1.2 Production planning under limited resources as an OR problem

Every manufacturer works within limits. In any month a plant can draw on only so many machine hours, so much material, a given number of workers and a store of a given size, while each product it could sell uses these inputs in its own mix and earns its own margin. Management therefore has to fix the output of each item for the coming period so as to earn the largest possible profit while staying inside every resource limit. If each unit always earns the same profit and each input is used in direct proportion to output, this is a linear programming problem (LPP). Kantorovich first framed

such problems in 1939 (English translation, 1960), Dantzig's simplex method made them solvable in practice, and by the late 1970s firms were using product-mix LP models in their policy decisions (Byrd & Moore, 1978).

LP suits this problem for two reasons. To begin with, management chooses only a small number of output levels but faces many more restrictions, so the plans that obey all of them form a convex region, and an optimal plan can always be found at one of its vertices (Dantzig & Thapa, 1997). In addition, the solver gives back more than the quantities to make. Every restriction comes with a shadow price, the extra profit an additional unit of that input would bring, and this turns the phrase “limited resources” into a figure a manager can use when buying. LP rests on four assumptions, namely proportionality, additivity, divisibility and certain (known) data (Hillier & Lieberman, 2005), and we return to them throughout Sections 3 to 7.

1.3 Method and structure

We chose two peer-reviewed case studies and read each one against a common checklist: the business setting, how the model is built, how it is solved, and a critical review. We worked from the complete papers, including their data tables and reference lists. Section 2 lists the two studies and Sections 3 and 4 review them in turn. Section 5 presents the general LP model, Section 6 contains our own re-solution and what-if tests on the feed data, Section 7 compares the approaches critically, and Section 8 gives our conclusions.

2. Selected Research Articles

Table 1. Articles analysed in this report

Paper	Reference	Domain	OR technique
A	Solaja et al. (2019), International Journal of Applied Operational Research, 9(3)	Manufacturing; animal-feed production (Nigeria)	Product-mix linear programme (4 products, 13 resource limits), solved with Management Scientist 5.0
B	Adebiyi, Amole & Soile (2014), Acta Universitatis Danubius. (Economica, 10(1)	Manufacturing; paint production (Nigeria)	Product-mix linear programme (5 products, 11 resource limits), solved with LINDO 11 with sensitivity output

The two studies use one technique on two genuine Nigerian plants. Paper A is a small model whose answer is surprising, while Paper B is bigger and draws on the solver's sensitivity output.

3. Analysis of Paper A: Production Planning in a Feed Mill

3.1 Real-life context

The firm studied is a mid-sized maker of livestock feed located in Abeokuta, Nigeria. Its four lines are layer mash, grower mash, broiler starter mash and broiler finisher mash, made from maize, soya beans, limestone, bone, wheat offal and a number of premixes. According to the authors, such firms usually decide output from past practice and gut feeling, so machines sit unused and inputs are wasted. The setting is agro-processing within manufacturing. OR fits well here: each input comes in a fixed monthly amount, the four feeds need these inputs in different quantities, and the choice of how many bags of each feed to make can be stated as a linear model with an exact solution.

3.2 Modelling and problem formulation

- **Objective:** the largest possible monthly profit across the four feeds, with each bag earning N207.25 (layer), N97.75 (grower), N128.75 (broiler starter) or N153.50 (broiler finisher).

- **Constraints:** thirteen “less than or equal to” limits, one per input (maize, soya beans, limestone, bone, wheat offal, fish offal, lysine, methionine, salt, three premixes and P.K.C.), each keeping monthly use within the stock on hand, e.g. 11,700 kg of maize and 2,600 kg of soya beans; no output may be negative.
- **Type of problem:** an LP product-mix model for one period with four variables, namely the number of bags of each feed.
- **Assumptions:** each bag earns a fixed profit and needs fixed amounts of input; input supply is capped at the monthly figures given; part-bags are allowed; and the company's recorded figures are correct.

3.3 Solution methodology

The figures were taken from the firm's own records, and the production manager explained entries that were unclear. The authors solved the model with the Management Scientist 5.0 package, which uses the simplex algorithm. They set the answer against what the firm was actually making, namely 40 bags of layer, 100 of grower, 25 of broiler starter and 70 of broiler finisher mash, a plan worth N32,028.75 each month. Only the optimal plan is given in the paper; it contains no sensitivity results and does not test the model on a second month.

3.4 Findings, impact and critical analysis

According to the solver, the firm should make 433.33 bags of layer mash and none of the other three feeds, which yields N89,808.33 a month compared with N32,028.75 today, an extra N57,779.58. The paper calls this an 80% rise, but working it out from the paper's own numbers gives roughly 180%, since 89,808.33 is about 2.8 times 32,028.75. For practice, the lesson is that a plan based on habit can be compared directly with an optimal one, and that making fewer products may be more profitable.

- **Strengths:** the model is simple to follow and uses genuine company data; the existing plan is used as a clear benchmark; and the software is cheap enough for a small firm.
- **Limitations:** with no demand or minimum-output limits, the single-product answer is not commercially realistic; the paper does not comment on soya beans being the only input that restricts profit; there is no sensitivity analysis; only one month of fixed data is used; and the text has some errors (mismatched table numbers, an extra fifth variable in the non-negativity condition, and the 80% figure noted above).
- **Extensions:** introduce sales ceilings and minimum outputs; model several months with stock carried forward; report shadow prices; treat profit and resource use as two separate goals; insist on whole bags.

4. Analysis of Paper B: Product-Mix Optimisation in Paint Production

4.1 Real-life context

Paper B looks at a Nigerian paint company with five products: Intra emulsion, Vinylmatt emulsion, Sandtex gloss, Intra gloss and texture paint. The authors comment that paint makers in Nigeria often follow fixed routines and rely on experience when deciding output. Management wants to know which of the five paints deserve a place in the plan, and how much of each, when materials, labour and plant capacity are all limited. The setting is paints and coatings manufacturing. OR applies because the products draw on the same scarce inputs and all the relationships are linear. The authors add that earlier product-mix studies were mostly theoretical or used made-up figures, so they chose to work with the firm's real records.

4.2 Modelling and problem formulation

The objective is the largest possible monthly profit, built from unit contribution margins of N690.66, N169.37, N2,188.74, N2,037.70 and N136.72 for the five paints in turn. Eleven restrictions appear in the printed model, covering water, titanium dioxide, calcium carbonate, binder resin, additives, colouring paste, sand, kerosene, pigment, labour hours and plant capacity, plus the usual non-negativity of output. The data table further mentions a market demand of 600,000 litres and storage space of 2,000,000 litres, yet neither of these is written as a constraint. The result is an LP

with five variables, built on fixed margins and input needs, using the firm's average monthly plan for 2012 and interview evidence.

4.3 Solution methodology

LINDO 11 was used to solve the model. It found the optimum after two iterations and printed a sensitivity table giving slacks and reduced costs, which the authors used to show how much cheaper a loss-making paint would need to become before it was worth producing. Before modelling, the researchers also interviewed company staff to learn how output had been planned up to then.

4.4 Findings, impact and critical analysis

Just two paints make it into the optimal plan, Intra emulsion and Intra gloss, giving the stated maximum profit of N6,479,833 per month. The paper gives reduced costs for the three paints left out: 153,222 naira for Vinylmatt, 118,756 naira for Sandtex and 266,875 naira for texture paint, i.e. how far each margin must improve before that paint is worth making. Our own solution of the printed model (Table 4, Section 6) gave the same optimum and agreed on two of these three values. For Sandtex our figure is close to 1,187,560 naira, exactly ten times the printed one, so a misplaced digit seems likely. We also found that just two restrictions are tight, calcium carbonate and kerosene, while the remaining nine are not fully used.

- **Strengths:** it uses actual company figures; the model is bigger than in Paper A; and the sensitivity results give managers extra insight, such as which paints are nearly profitable.
- **Limitations:** the demand and storage figures appear in the data but are missing from the model; units are confusing (profit is defined weekly in thousands of naira but discussed monthly, and outputs are written as 2,006,173 and 2,500,000 litres whereas the variables come out at 2.006 and 2.5); the plan is never compared with actual output; and only one period of fixed data is used.
- **Extensions:** include the demand and storage restrictions; carry out ranging on margins and input levels; insist on whole batches; and plan across several periods with inventory.

5. Mathematical Model: Linear Programme for Production Planning

The model given here is the usual product-mix LP, in the same form that both studies adopt: one variable per product and one “less than or equal to” restriction per scarce input.

Table 2. Notation

Symbol	Meaning
$i = 1 \dots m$	Resources: materials, labour hours, plant capacity ($m = 13$ in Paper A, $m = 11$ in Paper B)
$j = 1 \dots n$	Products ($n = 4$ in Paper A, $n = 5$ in Paper B)
x_j	Decision variable: quantity of product j made in the planning period
c_j	Profit (contribution margin) earned per unit of product j
a_{ij}	Quantity of resource i used by one unit of product j
b_i	Quantity of resource i available in the period
u_j	Upper limit on sales of product j (market demand)
l_j	Lower limit on output of product j (committed minimum); $l_j = 0$ if there is none
y_i	Shadow price of resource i : gain in Z from one extra unit of b_i

Formulation

$$\text{Maximise } Z = \sum_{j=1}^n c_j x_j \quad (1)$$

subject to:

$$\sum_{j=1}^n a_{ij} x_j \leq b_i, \text{ for each } i = 1 \dots m \quad (2)$$

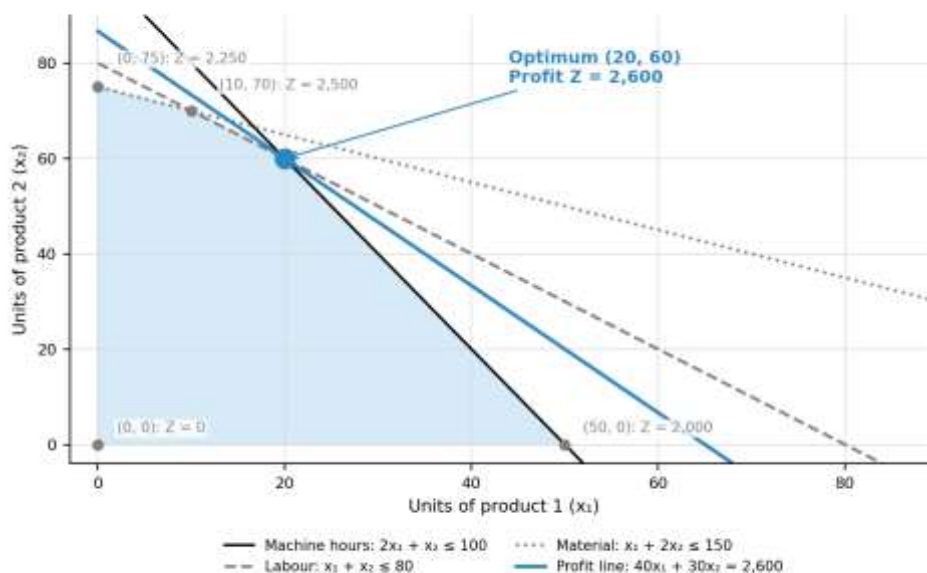
$$x_j \leq u_j, \text{ for each } j = 1 \dots n \quad (3)$$

$$x_j \geq l_j \geq 0, \text{ for each } j = 1 \dots n \quad (4)$$

In (1), profit is the margin of each product multiplied by its output and summed over all products. Constraint (2) caps the use of each input at the amount in stock; restrictions of this kind form the bulk of both published models (13 in Paper A and 11 in Paper B). Constraint (3) is a sales ceiling and (4) a guaranteed minimum output. Paper B reports a demand figure in its data yet omits (3) from its model, and (4) is absent from both. As the objective and all restrictions are linear, the set of allowed plans is a convex polygon when there are two products and a polyhedron when there are more, so any optimum lies at a vertex. The simplex algorithm moves along vertices, raising Z with every move. In the optimal plan, an input with a positive shadow price y_i is used up completely and is what restricts profit, while an input with some left over has a shadow price of zero. Each product excluded from the plan has a reduced cost, which is how much its margin must increase before it is included.

Figure 1 shows the idea for two products with invented data: profits of 40 and 30 per unit, machine hours $2x_1 + x_2 \leq 100$, labour $x_1 + x_2 \leq 80$ and material $x_1 + 2x_2 \leq 150$. The feasible region has five corner points. The best of them is (20, 60) with $Z = 2,600$, where machine hours and labour are both used up and material has 10 units to spare.

Figure 1. Graphical solution of a two-product production plan



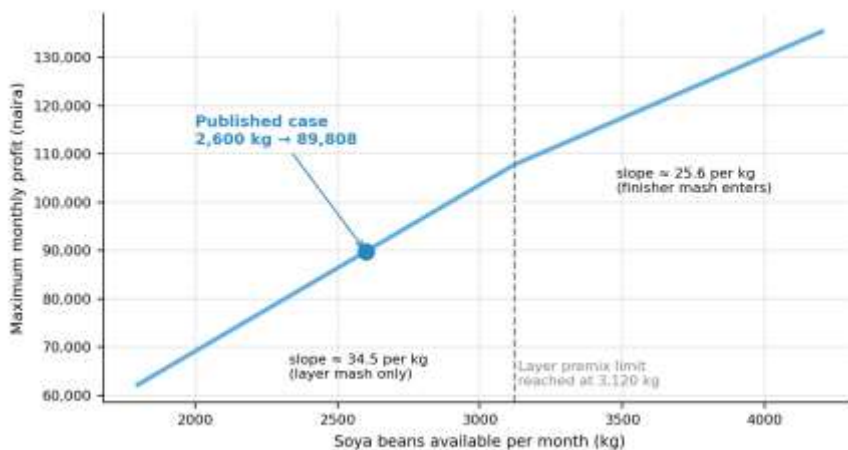
Illustrative data. The shaded area is the feasible region; its best corner point is where machine hours and labour both bind.

6. Extension: Re-solving and Stress-Testing the Feed-Mill Model

Each paper gives one optimal plan and stops there. To take the analysis further, we typed the coefficients printed in Paper A into an LP solver (SciPy in Python, using the HiGHS algorithm). The input numbers belong to the original authors; the what-if cases and the shadow-price discussion are our own work.

Our first step was to confirm the paper's answer. The solver again gives 433.33 bags of layer mash and N89,808.33 profit per month. Soya beans are the only input that runs out, with all 2,600 kg consumed; every other input is left over (for instance, 5,850 kg of maize is unused). Soya beans carry a shadow price of roughly N34.54 per kg, equal to the N207.25 earned on a bag of layer mash divided by the 6 kg of soya each bag contains. Under the firm's present plan only about 49% of the soya stock is used, so most of the model's improvement comes simply from using this scarce input fully. Table 3 traces how the answer moves as the planning rules or the soya supply are altered.

Figure 2. Feed-mill model: optimal profit as soya-bean supply changes



Re-solved from the data published in Paper A; all other resources held at their published values.

Table 3. Feed-mill plans under different rules (bags per month; profit in naira)

Scenario	Layer	Grower	Starter	Finisher	Profit	vs current
Company's current plan	40	100	25	70	32,028.75	—
Published optimum	433.33	0	0	0	89,808.33	+180.4%
At least 20 bags of every feed	376.67	20	20	20	85,664.17	+167.5%
Current quantities kept as minimums	261.25	100	25	70	77,882.81	+143.2%
Each feed capped at 150 bags	150	150	19.23	150	71,250.96	+122.5%
Soya beans +10%	476.67	0	0	0	98,789.17	+208.4%
Soya beans +25%	520	0	0	21.67	111,095.83	+246.9%

Source: published data of Paper A re-solved by the authors of this report. "Starter" and "Finisher" are the broiler starter and broiler finisher mashes.

Insisting on a minimum of 20 bags of each feed lowers profit by only about N4,144 a month relative to the published optimum, which is small next to the gain over today's plan, so a wider product range is affordable. Holding today's quantities as minimums lowers profit by about N11,926. Increasing soya beans by 10% (260 kg) raises profit by N8,981, as the shadow price predicts. At +25%, however, the stock of layer premix limits layer mash to 520 bags, finisher mash comes into the plan and profit grows more slowly (Figure 2). The soya shadow price is therefore valid only over a certain range, something Paper A's single answer cannot reveal.

Table 4 repeats this check for Paper B. Our optimum and two of the reduced costs agree with the paper; the third reduced cost and the units do not, and the paper never says which restrictions are binding.

Table 4. Paper B: printed results compared with our re-solve

Item	As printed in Paper B	Our re-solve
Maximum profit (naira)	6,479,833	6,479,833
Intra emulsion (X1)	2,006,173 “litres”	2.006 model units
Intra gloss (X4)	2,500,000 “litres”	2.5 model units
Reduced cost, Vinylmatt (naira)	153,222	153,222
Reduced cost, Sandtex (naira)	118,756	1,187,560
Reduced cost, texture (naira)	266,875	266,876
Binding limits	Not reported	Calcium carbonate; kerosene

Unit basis follows the paper (margins in thousands of naira). The printed X1 and X4 figures read like 2.006,173 and 2.500,000 written with European-style separators.

7. Critical Reflection

Table 5. Comparison of the approaches

	Paper A (feed mill)	Paper B (paints)	Our what-if analysis
Decides	How many bags of each feed to make per month	Which of five paints to make, and how much	How the feed-mill plan changes under other rules or resource levels
Objective	Maximise monthly profit	Maximise monthly profit (contribution)	Maximise profit under each added rule
Method	Linear programming, Management Scientist 5.0	Linear programming, LINDO 11 with sensitivity report	Linear programming re-solved with HiGHS; shadow prices and scenarios
Main weakness	No demand limits; one-product plan; no sensitivity analysis	Demand and warehouse limits left out; unclear units	Relies on published data we could not check; one month only

7.1 Strengths of the modelling approach

An LP model captures the production trade-off in very little space: a few variables and one restriction per input. As both studies demonstrate, ordinary software solves it in seconds, and managers can follow the output. The most valuable results are the shadow prices and reduced costs, since they point to the input worth buying more of and the product best dropped. Our re-run of Paper A makes this plain: profit was held back by soya beans, not by machine time or any other input.

7.2 Limitations and assumptions

The LP model treats margins and input needs per unit as fixed and allows output in fractions, but in practice prices and costs change and feed is packed in whole bags or batches. Neither paper models demand, so the optimal plan may lean on one or two products that buyers might not take in those amounts. Each study uses one month from one company, and neither checks the advice against the firm's later output. Lastly, the small errors we found in table numbering, units and one reduced cost show that mistakes can slip through review; we could only spot them because the coefficients were published in full.

7.3 Possibilities for extension

Obvious improvements would be to add demand ceilings and minimum outputs, to plan over several months with stock and staffing carried forward, to require whole bags or batches, and to use goal programming where profit is not the sole target. Since prices and input costs are uncertain, robust or stochastic LP could show how dependable a recommended

plan is. The work also connects to scheduling: after the mix is fixed, PERT/CPM could time the production run and estimate the chance of finishing by a deadline. Testing any model against real plant data would turn its advice into proof.

8. Conclusion

Deciding output when resources are scarce is the textbook application of LP, and the two studies show the method used in actual plants. Paper A converts a feed firm's monthly input stocks into a plan that earns well above its current one, although the single-product result shows why demand limits are needed. Paper B deals with five paints and eleven resource limits and uses sensitivity output to show which paints are not yet profitable. Both rest on the same structure of a profit objective, resource limits and non-negative output, and our re-solution of the feed data shows that a single scarce input decides the result and that the advice is valid only within a range. Three lessons stand out: shadow prices are as important as the plan, a missing constraint can make an optimal answer unworkable, and the next useful step is to add demand, time and uncertainty to the model.

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